Boosting Estimation Accuracy of Low-Cost Monopulse Receiver Via Deep Neural Network

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***Abstract*— In this paper, a low-cost monopulse receiver is presented to achieve high accuracy of angular estimation by applying deep neural network. The low-cost receiver is composed of a 4 - element patch array, a planar comparator network, and a down conversion module. Different from other signal processing methods, a deep neural network is developed for proposed low-cost monopulse receiver, which can map the misaligned target angular positions in the measurement to the actual physical location under detection.**

Keywords—deep neural network, low-cost monopulse radar, angular estimation.

I. Introduction

Monopulse tracking radar is widely applied in airborne radar, autonomous driving, medical diagnostics, and low cost IoT, where the monopulse antenna array decodes the impinging RF signal to precise angular information of targets under detection. To be specific, the received RF signals from 2D antenna array in monopulse receiver are processed through comparator network in electromagnetic waveform domain to find the location and velocity of moving object [1]-[6]. However, under multipath propagation condition, the direct amplitude or phase comparison of sum and difference signal from monopulse array is ineffective and causes misalignment error due to amplitude and phase distortion. The calibration and correction steps [7]-[9] may mitigate the angular estimation error, which requires extra computation effort in low-cost system. Moreover, utilization of thin metamaterial absorbers [10]-[11] could also be useful to remove multi-path propagation effect. In recent years, deep neural network (DNN) learning attracts great interest which can extract features from covariance matrix to construct nonlinear mapping [12], and the deep learning-based classification of radar targets has been extensively studied in [13]. For example, in [14], a DNN for the estimation of directional of arrival is proposed where the input is the covariance matrix to preserve part of the useful information. Up to now, there is limited study on merging deep neural network into monopluse array to boost the estimation accuracy, especially for low-cost system with limited computation resources.

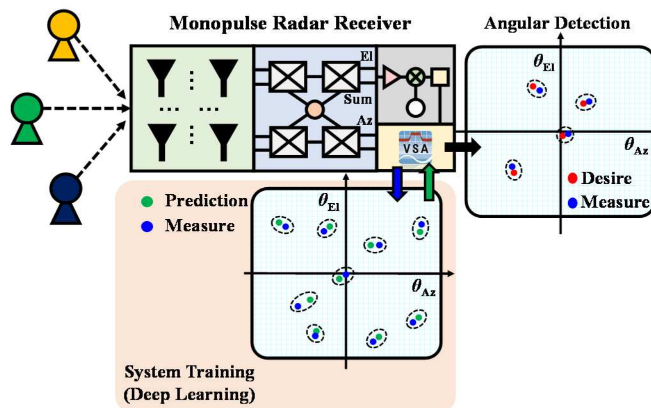

Fig. 1 Proposed low-cost monopulse receiver schematic diagram with DNN.

In this paper, a deep neural network (DNN) is customized to low - cost monopulse receiver system using small size data set and achieving fast training process. Due to the capability of establishing highly nonlinear relationships from the inputs to the outputs, the proposed DNN can accurately predict the physical location of tracking object in milliseconds.

II. Design of Proposed Monopulse

The proposed low-cost monopulse receiver system with DNN is shown in Fig. 1. It is composed of a four-quarter 2D antenna array, a planar comparator network, a down-conversion link, and a baseband analyzer module. The output signals from the low-cost monopulse array are captured and analyzed by Keysight Vector Signal Analyzer (VSA). The system is trained by deep learning algorithm with small amount of measurement data and deployed to real angular measurement.

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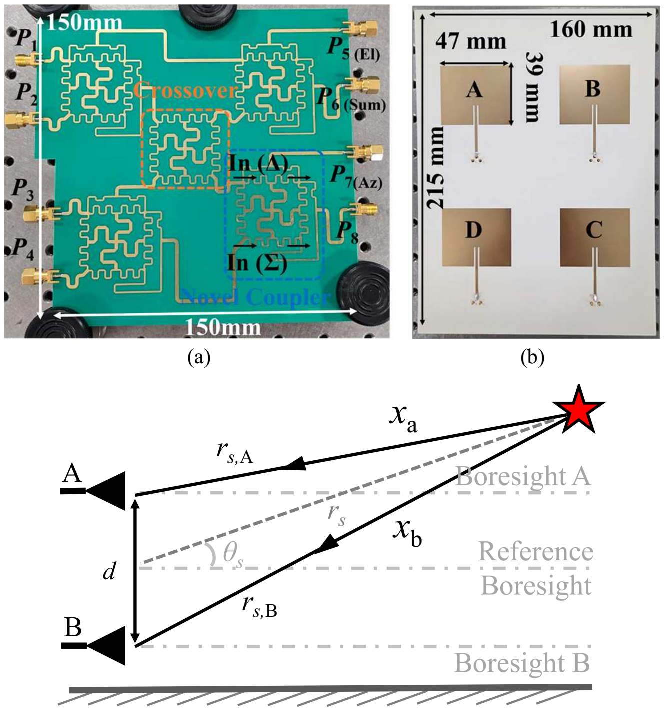

Fig. 2 Proposed monopulse array (a) planar comparator network (b) 2 × 2 patch antenna array, (c) DoA estimation through proposed monopulse radar.

A. Low-Cost Planar Monopulse Receiver Array Design

Fig. 2 (a) shows the proposed low-cost monopulse comparator network designed at 2GHz, which consists of four planar 180° rat-race couplers and a zero-phase delay crossover. The planar rat-race coupler is designed with symmetrical structure where the input ports (Σ and Δ) are not crossing with output ports, which is totally different from the conventional rat-race coupler. In addition, a planar crossover [15] is applied to interconnect two stages of couplers with zero phase distortion, which can further improve the loss and bandwidth of proposed comparator network. In addition, a 2 × 2 patch antenna array operating at 2GHz is designed as in Fig. 2 (b), where each patch element is positioned half-wavelength away from each other to avoid the mutual interference. By integrating the comparator network and 2D antenna array, the proposed monopulse array is realized with low cost, planar, and low amplitude phase imbalance.

B. Estimation of Angular Information

Amplitude or phase comparison is a typical method to estimate the angular information of detecting target. In this low-cost monopulse receiver, phase comparison method is applied due to planar antenna structure providing the identical boresight direction. As shown in Fig. 2 (c), a two-element linear array separated by d can determine the angle of arrival from

$$r_{s,A(B)} = r_s \mp \frac{d}{2} \cdot \sin\theta_s \tag{1}$$

Where θ_s is direction of arrival (DoA) of the target from the reference boresight direction, and r_s is target distance from array center. The echo signal received at two antennas (A & B)

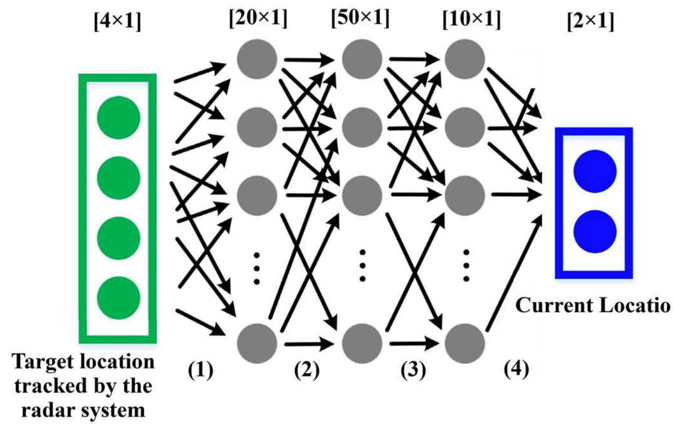

Fig. 3 Implemented Deep Learning Network architecture. The input of the network is consisting of elevation and azimuth angles, horizontal and vertical position of the target. The output of the network is the corrected elevation and azimuth angles of the target.

can be expressed as

$$x_{a(b)} = e^{-j\frac{2\pi}{\lambda}\cdot(2r_s \mp \frac{d}{2}\sin\theta_s)} \tag{2}$$

and the difference and sum of signals received by A and B can be derived as

$$\Delta = x_a - x_b = -2j \cdot e^{-j\frac{4\pi r_s}{\lambda}} \cdot \sin(-\frac{\pi}{d}\sin\theta_s) \tag{3}$$

$$\Sigma = x_a + x_b = 2j \cdot e^{-j\frac{4\pi r_s}{\lambda}} \cdot \cos(\frac{\pi}{d}\sin\theta_s) \tag{4}$$

The angular information of arrival signals can be calculated based on the ratio (γ) of difference to sum signals, given by

$$\gamma = \frac{\Delta}{\Sigma} = j \cdot \tan(-\frac{\pi d}{\lambda} \cdot \sin\theta_s) \tag{5}$$

Similarly, the angles in two dimensions are evaluated from equations (1) - (5) by placing 2D antenna array in quadrant. To be specific, the extracted signals are denoted as sum (Σ) and difference (Δ_{Az}, Δ_{El}, and Δ_{Del}), which are computed in analog form through monopulse comparator network as:

$$\Delta_{Az} = (A + D) - (B + C) \tag{6}$$

$$\Delta_{El} = (A + B) - (C + D) \tag{7}$$

$$\Delta_{Del} = (A + C) - (B + D) \tag{8}$$

$$\Sigma = (A + B + C + D) \tag{9}$$

Then, monopulse ratio at two dimensions can be derived as:

$$\frac{\Delta_{Az}}{\Sigma} = \tan\left[\frac{\pi d}{\lambda}\sin(\theta_{Az})\right] \tag{10}$$

$$\frac{\Delta_{El}}{\Sigma} = \tan\left[\frac{\pi d}{\lambda}\sin(\theta_{El})\right] \tag{11}$$

C. Merging Deep Neural Network

The goal of DNN is to find the accurate location through the monopulse receiver and compare with carry-on real-time monitoring of accurate data with minimum delay. The input for the neural network is elevation (θ_{El}) and azimuth (θ_{Az}) angles estimated by the proposed low-cost monopulse receiver. Here, the effect of the distance between the radar and the object is also considered to the input data of the network. Therefore, the input layer of DNN is a 4×1 matrix, and it generates corrected elevation and azimuth angles. As in Fig. 3, the DNN consists of three consecutives fully connected hidden layers, each containing 20, 50, and 10 hidden neurons, respectively. During the training process, the weights, and biases in hidden layers of DNN are optimized to minimize the loss function of:

$$Loss_{DNN} = \frac{1}{N} \sum_{i=1,2,\ldots,N} [(\theta_{El\_DNN} - \theta_{El\_truth})^2 + (\theta_{Az\_DNN} - \theta_{Az\_truth})^2] \tag{12}$$

where $\theta_{\text{El\_DNN}}$ and $\theta_{\text{El\_truth}}$ are the elevation angles of DNN and true location, respectively. Similarly, $\theta_{\text{Az\_DNN}}$ and $\theta_{\text{Az\_truth}}$ are the azimuth angles of DNN and true location, respectively. N is the number of samples. Without loss of generality, we chose the distance between the object and the monopulase receiver array to be 620 mm. The dataset for training the DNN contains 100 samples of randomly chosen locations of the target. In this work, for the sake of simplicity, only one distance between object and radar is measured and analyzed. However, the proposed DNN has the capability to correct the radar with different distances by considering the cost associated with collecting more data samples for training. The true and predicted location of the object in a 2D plane is recorded as four parameters: elevation and azimuth angles, and vertical and horizontal distances from the center of the 2D plane. 90% of the data set is allocated for training, while the remaining 10% is reserved for validation. The horizontal and vertical calibration in this system is carried out with one DNN and combined. Therefore, the two-coordination data are added to the input and output of the DNN, which reduces the system's complexity as it calibrates the information with one DNN (instead of using two DNNs to predict both vertical and horizontal misalignments). Furthermore, misalignment in each coordination might be relative to the target's actual location in the other coordination. Accordingly, using one DNN for both coordination can provide more accurate results.

III. Simuation and Experimnet validation

To estimate the angular information of object, the monopulse receiver is designed by integrating the proposed monopulse array with Keysight U3851A microwave kits which converts the RF signal to low frequency signal for sampling. The testbed setup is shown in Fig. 4, where it includes a 2 GHz standard patch antenna fed by signal source which behaves as the transmitter. The proposed monopulse receiver is positioned at a far-field distance (> 0.5m) to capture the RF signals (Δ_{Az}, Δ_{El}, and Σ), and the received RF signal are down converted into baseband signals at 100MHz. The Keysight vector signal analyzer (VSA) is applied to analyze the angles in two dimensions. Specifically, the transmit antenna is moved along horizontal and vertical, and the angular information is measured and estimated using equations (10) and (11). The training process takes 5 minutes for a laptop using Intel® Core™ i7-12700H Processor with 20,000 of iterations. We chose Adam optimizer to update the weights and biases of the DNN. After DNN is fully trained, the validation error is 1.2×10^{-6}, equivalent to a position error of 0.68 mm in a 2D plane with a 620 mm distance from the transmitter. The accuracy could be enhanced using either a bigger training data set or antenna array with larger number sub-elements that can capture more information of the target. Fig. 5 shows several predicted samples where the angular estimation after DNN (green dot) is close to physical location (orange dot) of target. Once the DNN is trained, it can provide accurate locations in a few milliseconds which enables real time tracking for the radar system. In future works, a system that can detect the target even when obstructed by various obstacles, such as the human body, could also be developed.

Fig. 4 DoA estimation using proposed monopulse receiver system.

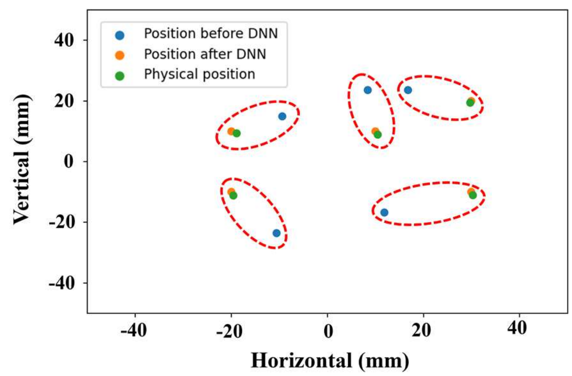

Fig. 5 Predicted samples versus the tracking radar estimations and the object's true positions. Each dotted circle represents one sample.

IV. Conclusion

In this paper, we introduce low-cost monolulse radar with high angular estimation accuracy leveraging a deep neural network. A prototype testbed merged with DNN is designed to demonstrate the effectiveness of proposed system. Different from any other tracking radar, integrating DNN into low-cost monopulse array can realize fast training and real-time monitoring of angular information using small amount of data samples.

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